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Impact assessment of spatial resolution on landslide inventories: A case study of Muzaffarabad city

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Abstract

Using different resolution data, a number of scientists have developed landslide inventories after Kashmir earthquake (7.6 Mw), which triggered thousands of landslides in Muzaffarabad and Balakot. However, the impact of image spatial resolution on landslide inventory is less explored. This study aims to evaluate the impact of image spatial resolution on landslide inventories. Five different resolution images including, Worldview-2, SPOT-5, Sentinel-2, ASTER and Landsat-8 were used to compute landslide inventory for the 2005 Kashmir earthquake affected area. Support Vector Machine (SVM) classifier was used to classify the acquired images and derived landslide inventory. Number of landslides and covered area from different sensors were computed. Accuracy assessment of the developed inventories was performed for each of developed landslide inventory. The result shows that with increase in image spatial resolution the number and area of landslides increases. The recently lunched freely available data of Sentinel-2 with spatial resolution of 10 m is good source of dataset for regional based landslide inventory developing and landslide susceptibility mapping. The study shall assist the researchers to select an optimal remote sensing images for developing landslide inventory; and subsequent hazard assessment and mitigation.

Keywords: Landslide inventories, Muzaffarabad city, Kashmir earthquake.

1. Introduction

Natural hazards have devastating impacts on the socio-economic development worldwide. Landslide is one of the major natural hazards, in the mountainous region, with negative impacts on economy and society (Kamp et al., 2008). Frequent landslide in northern Pakistan, can be attributed to active seismicity, monsoon rains, rough terrain, deforestation and anthropogenic activities on unstable slopes (Kamp et al., 2008; Shafique et al., 2016; Hewitt, 2009; Jones et al., 1983). Earthquakes and rainfalls are considered as the major triggers for widespread distribution of landslides (Wasowski et al., 2011; Tang et al., 2011). Spatial distribution and intensity of landslides are mainly controlled by landslide causative factors including, topography, geology, tectonics, geomorphology, hydrogeology, land use / land cover and anthropogenic activities (Sato et al., 2007; Dai and Lee, 2002; Kamp et al., 2008; Owen et al., 2008). Development of landslide inventory is the first and crucial step in landslide hazard assessment (Owen et al., 2008). Reliability of landslide hazard maps, is mainly determined by the accuracy of the derived landslide inventory.

Remote sensing and GIS are effective tools for landslide mapping, monitoring, susceptibility, hazard, vulnerability and risk assessment, from local to regional scale (Shafique et al., 2016; Singhroy, 2009) . Landslide inventories are usually developed from satellite images through manual digitization, pixel based digital classificaiton and object based image classificaiton (Martha et al., 2010; Lodhi, 2011; Basharat et al., 2016). Pixel based digital image classification techniques, such as supervised (Escape et al., 2014), unsupervised (Borghuis et al., 2007) and support vector machine techniques (Yao et al., 2008) are used for mapping landslides. Support vector machine classifier is considered as the appropriate technique for image classification, since it works on very less number of training classes (Momeni et al., 2016; Pal and Mather, 2005). Spatial resolution of an images is crucial for determining the size and extent of detectable landslides and are therefore considered critical for developing an accurate landslide inventory (Shafique et al., 2016). Moderate resolution satellite images, such as the ASTER and Landsat are frequently used for landslide mapping at a regional scale (Kamp et al., 2008; Lodhi, 2011), but due to their coarse resolution and consequently smoothening effect, limit their application for mapping small landslides (Shafique et al., 2011). Fine resolution images such as the Worldview, IKONOS and Quick bird are capable of detecting small landslides (Chini et al., 2011; Saba et al., 2010), though, their high price and narrow swath size, limit their utilization for developing landslide inventory at a regional scale (Shafique et al., 2016). To the best of our knowledge, so far, the impact of image spatial resolution on derived landslide inventory has not being explicitly assessed.

The availability of satellite images with wide array of resolutions, it vital to evaluate the impact of image-spatial-resolution on the accuracy of landslide inventory. The aim of this study is to develop landslide inventories from the most frequently utilized satellite images, using SVM technique, and evaluate the impact of image resolution on the accuracy of the derived landslide inventory.

2. Material and methods

2.1 Study area

The study area is located in Muzaffarabad district that was severally devastated by the 2005 Kashmir earthquake. The selected study area is prone to frequent landsliding mainly due to rough terrain, fractured geology, tectonic faults, monsoon rains and anthrolpogenic activites on unstable slopes. The location map of the selected study area is shown in Figure 1.

Landsliding is a common phenomanon in northren Pakistan due to active seismcity, rough topography, monsoon rains, deforestation and infrastructure development on unstable slopes. The 8th October 2005 Kashmir earthquake, has severally devastated the northern Pakistan and Kashmir region. The Kashmir earthquake, has trigerred thousands of landslides that were distributed throughout the affected area of >7500 km^2 (Owen et al., 2008). The earthquake induced landslides have resulted in around 1000 direct fatalities and many more occured indirectly due to the lack of first aid and disruption in communication networks (Petley et al., 2006; Kamp et al., 2008). The earthquake induced extensive fissuring and cracks on slopes make the region vulnerable to landslides in future (Owen et al., 2008).

2.2. Data set

For developing landslide inventory, Worldview-2, Sentinel-2, SPOT-5, ASTER and Landsat-8 images were used in this study (Table 1).

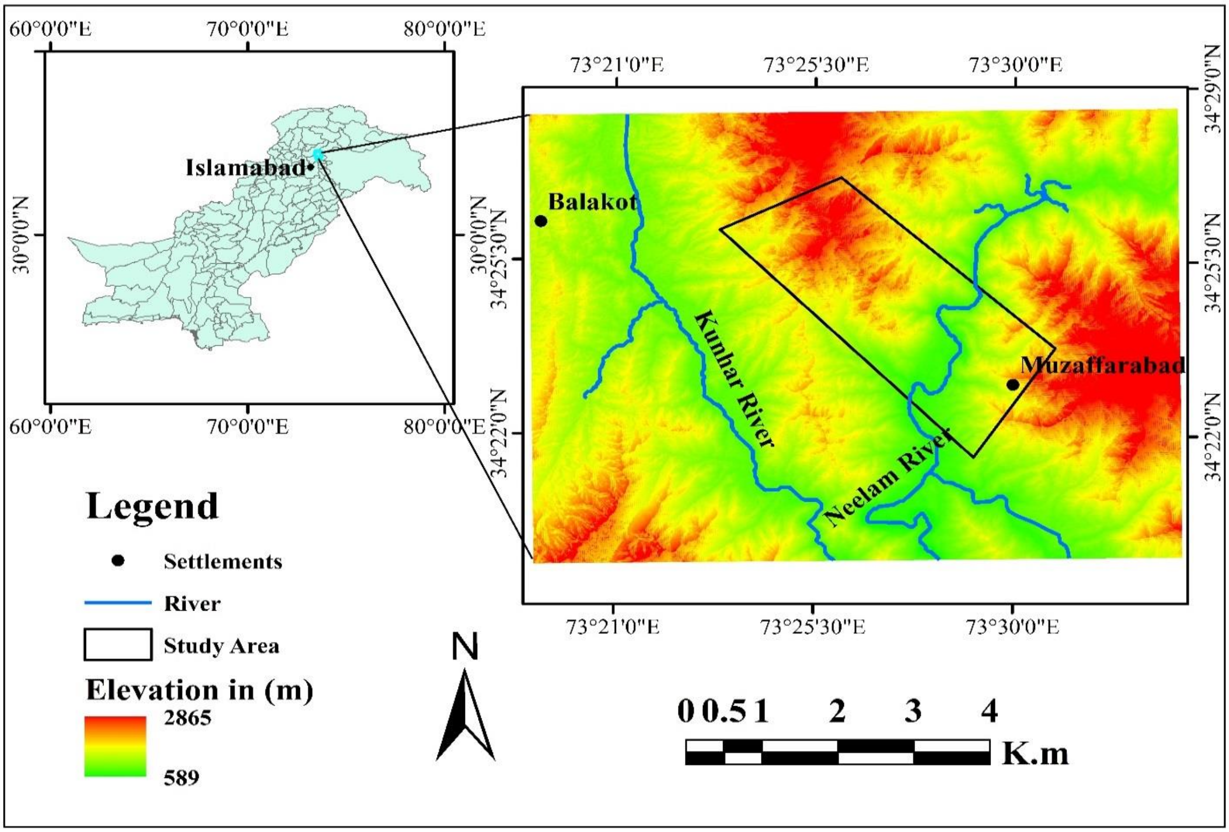

Fig. 1. Location map of study area.

Table 1. Characteristics of the satellite images used in the study.

Sensor/Satellite	**Spatial Resolution**	**Acquisition date**
Worldview 2	0.4 m	12th June 2015
Spot-5	2.5 m	26th June 2015
Sentinel-2	10 m	23th August 2015
ASTER	15 m	23rd September 2015
Landsat-8	30 m	24th July 2015

The Worldview-2 image with spatial resolution of 0.4 m was selected as the most fine resolution image to derived landslide inventory for the study area. The natural color composite (band 1, 2 and 3) was used for detecting the landslides. The SPOT-5 image with 2.5 m spatial resolution was acquired and the atmospheric and geometric corrections were applied subsequently. The band composite of 3, 2, and 1, was used for the detection of landslides. The recently launched and freely available, Sentinel-2, with spatial resolution of 10 m and temporal resolution of 5 days, provide an excellent data source for landslide inventory and monitoring of landslides (Casagli et al., 2016). The image preprocessing, including atmospheric and geometric corrections were applied on Sentinel-2 image. The band composite of 2, 3 and 4, was used for detecting landslides from the Sentinel-2 image. The Advanced Space borne Thermal Emission and Reflectance Radiometer (ASTER) derived images are effectively used for mapping earthquake induced landslides (Lodhi, 2011). The bands (1, 2, and 3) acquired in the visible portion of the spectrum with spatial resolution of 15 m, were used for mapping the landslides in the study area. The Landsat-8 image with spatial resolution of 30 m was used for developing landslide inventory (Mwaniki et al., 2015). Preprocessing techniques of radiometric and atmospheric corrections were applied to the acquired Landsat-8 image. The band composite of 7, 3 and 2, was used for detecting the landslides for the study area. The acquired images were preprocessed and classified in the ENVI 5.3 software.

2.3. Landslide inventory

To develop the landslide inventory, Support Vector Machine (SVM) was used to classify the acquired satellite images. To evaluate the impact of spatial resolution on landslide inventory single classifier (SVM) was used for all the images. To compute the landslide inventory, land cover maps comprised of various classes (e.g., landslides, barren land, settlement, water bodies and vegetation) were developed from the images acquired by various sensors. The class "landslide" was vectorized and cross validated with their actual image and Google Earth image. Furthermore, to evaluate the impact of spatial resolution on derived landslide inventories, numbers of landslides and covered areas (in km^2) were computed from all the developed landslide inventories.

2.4. Support vector machine

Support vector machine (SVM) is considered an accurate classification algorithm (Pal and Mather, 2005) and differentiate classes from one another on the basis of hyperplane which separate different classes from one another (Mountrakis et al., 2011). Optimal separation hyperplane is often used to maintain the decision boundary that minimizes mis-classifications (Mountrakis et al., 2011).

To classify an image, SVM demands limited number of training data. In this study, 13 training samples were collected for every land cover class. The image was subsequently classified using SVM classifier implemented in ENVI 5.3 software.

2.5. Accuracy assessment

To evaluate the reliability of the landslide inventories, accuracy assessment was performed for each of the developed landslide inventory. In this study, 117 landslide reference points were collected from the field and were used to evaluate the accuracy of the developed landslide inventory.

3. Results

3.1. Impact of spatial resolution on landslide inventory

The landslide inventories derived from different resolution images show that the Worldview 2 image (0.4 m resolution) has detected the highest number of landslide and the Landsat-8 image (30 m resolution) has detected the minimum number of landslides (Table 2).

Utilized images of all the 5 sensors and the corresponding derived landslide inventories are shown in figure 2. Relatively large size landslides were detected in all sensors images, however, the landslides smaller than the pixel size of an image were not detected. Both the number and area of landslides decreased with decrease in spatial resolution (Table 2). Only 17 landslides (with minimum area coverage of 0.06 km^2) were mapped in all resolution images, but small landslides (with area of less than 5 m^2) were only detected in Worldview-2 imagery. The Worldview-2 derived landslide inventory cover an area of 4.83 (km^2) and Landsat-8 derived landslide inventory cover an area of 2.81 (km^2). The number of landslides mapped by every dataset, total covered area and minimum/maximum covered area of landslide is given in (Table 2)

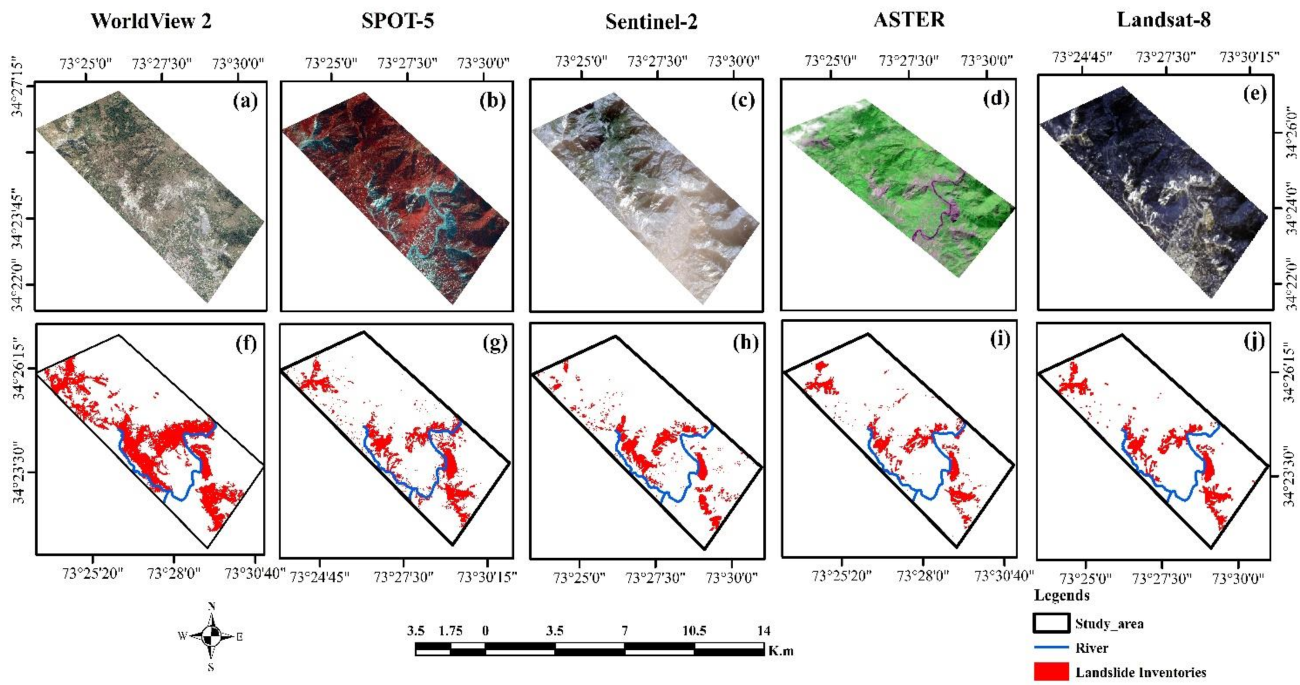

Fig. 2. Different resolution imageries and their corresponding landslide inventories.

Table 2. Calculated number and covered area of landslides

Sensors	Number of Landslides	Total covered Area by Landslide (Km^2)	Landslide Minimum Area in (m^2)	Landslide Maximum Area in (m^2)
Worldview-2	36592	4.83	2.01	1122300
SPOT-5	2421	4.16	6.24	985120
Sentinel-2	688	3.43	100	382640
ASTER	299	3.04	241	447600
Landsat-8	109	2.81	900	618500

The decline in the landslides area mapped with decrease in spatial resolution of imagery is graphically shown in figure 3. Due to smoothening and averaging of the area with decreasing image resolution, the capability of image to detect the landslides smaller than the corresponding image resolution is also decreasing. Therefore, the relatively coarse resolution images, such as Landsat-8, cannot detect the landslides with area of less than 900 m^2. Hence, the inventories derived from these coarse resolution images underestimate the potential landslide hazards in the area. The fine resolution Worldview2 can detect the landslides with area of > 0.4 m, resulting in more detailed inventory. However, because of its fine resolution, it is also prone to map non-landslides features such as (river bank, barren land and roof of building) as landslides, because of their similar spectral reflectance with the landslides. Hence, the landslide inventory derived from the Very High Resolution (VHR) images, such as Worldview-2 might over-estimate the prevailing landslide hazard in the area. Eventually, the landslide inventory developed from the VHR images needs to be validated in the field to rectify the errors and develop a comprehensive and accurate landslide inventory.

For mapping landslide, the impact of spatial resolution of an image is shown in figure 4. The spatial extent and area of landslide can be quantified more precisely using high resolution images.

In figure (4), using Worldview-2 image, the covered landslide area was 0.033 km^2 while Landsat-8 (relatively course resolution) detected the same patch equal to 0.015 km^2.

The results clearly shows that the spatial resolution has high impact on landslides inventory as from table 2 the total covered area by landslide is 4.83 km^2 and the minimum mapped landslide has the area of 2.01 m^2 and the course resolution data used for this study has mapped 2.81 km^2 and the minimum landslide mapped by Landsat-8 data is 900 m^2. Area covered by every dataset is plotted in figure 5.

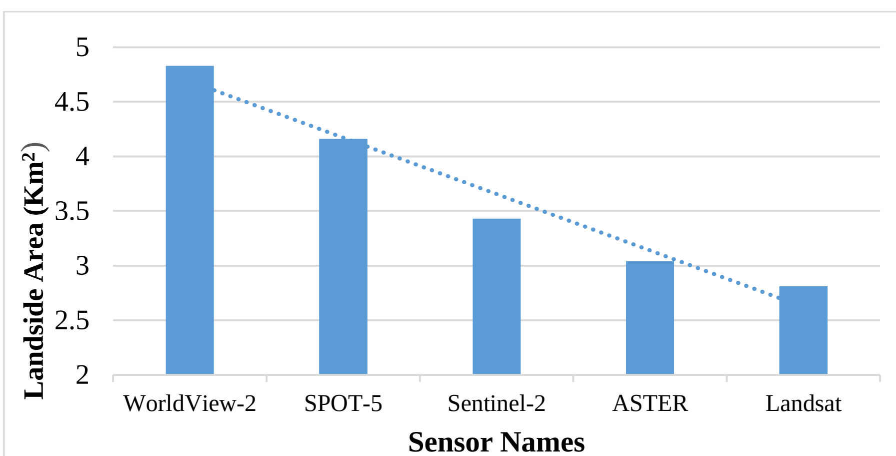

Fig. 3. Covered area of all the landslides in study area of all the datasets.

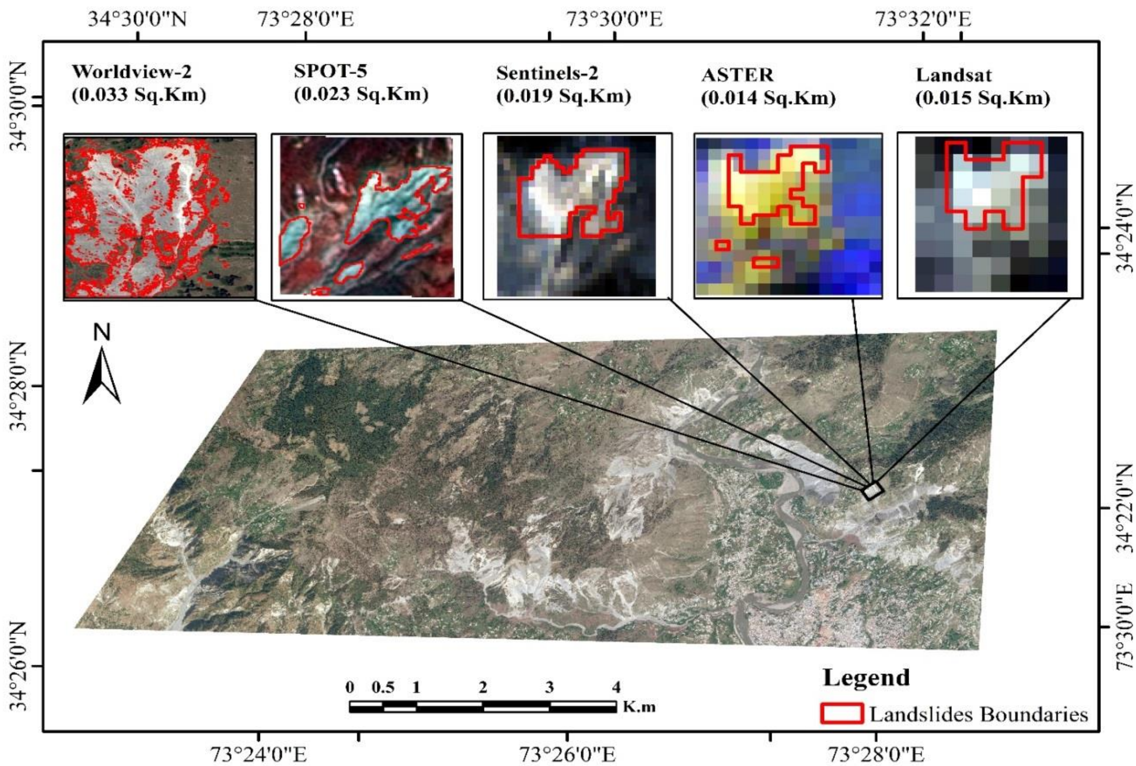

Fig. 4. Comparison of mapped landslide in different spatial resolution datasets.

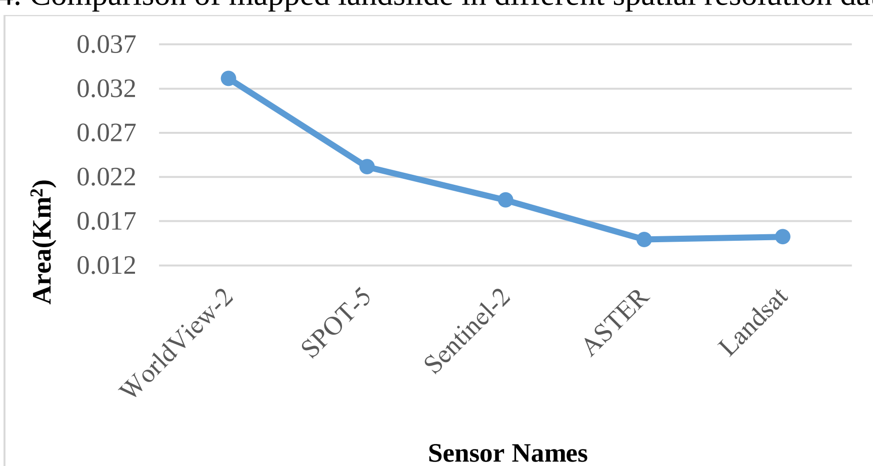

Fig. 5. Covered area of landslide in small patches.

Table 3. Accuracy assessments of landslide inventories.

Datasets	Total Points	Correctly Overlaid Points	Overall Accuracy (%)
Worldview 2	117	112	95.72
SPOT-5	117	85	72.64
Sentinel-2	117	77	65.8
ASTER	117	68	58.19
Landsat-8	117	69	59

3.2. *Accuracy assessment*

Accuracy assessment is an essential component of any research specifically for the remote sensing approach. We validate of results with the field data to find the accuracy of our research work. Table 3 shows us the accuracy in percentage.

The landslide inventory computed from the Worldview-2 data result in highest accuracy of 95.72 %, followed by SPOT-5 with 72.64%. The ASTER and Landsat-8 derived inventory has accuracy of around 59%.

4. Discussion

This study aims to evaluate the impact of image spatial resolution on derived landslide inventory. It is observed that spatial resolution of the utilized satellite images has significant impact on the derived landslide inventories. Using fine spatial reslution Worldview-2 data, 36592 landslides were detected in an area of 50.12 km^2 . In recent past, Saba et al. (2010) used Worldview-1 data for the landslide inventory in the same study area and mapped 154 landslides from total area of 36 km^2 the discrepancies in both studies is the mapping techniques, the current study has used semi-automatic technique to map the landslides and (Saba et al., 2010) have mapped the landsldies manually. The Worldview-2 imagery has a capability to detect small landslides (i.e., in this study the Worldview-2 data have minimum landslide coverage area equal to 2.01 m^2). The course resolution data used in this study is Landsat-8 having spatial resolution of 30 m, which has mapped the minimum area of 900 m^2. Landsat-8 data couldn't map the landslides having area less than 900 m^2. Both the number of landslides and area decreased with decreasing the spatial resolution (Table 2). Fine resolution images leads to higher accuracy, however, their high costs and narrow swath size limit their application for regional studies. Therefore, Sentinal-2, ASTER and Landsat-8 with their global coverage and free availability can be used for developing landslide inventory which in-turn is useful for landslide susceptibility and hazard assessment.

Subsequent to the Kashmir earthquake, various studies have developed landslide inventories using different satellite images. Owen et al. (2008) used the post-earthquake ASTER image with an area 750 km^2 and mapped 1293 landslides using visual image classification techniques and field observations. Kamp et al. (2008) has utilized ASTER imagery to develop landslide inventory using visual based image classification technique and mapped 2252 landslides covering the area of 2250 km^2 and validated from field observation. Kamp et al. (2008), Owen et al. (2008) has developed landslide inventory using the ASTER data with visual based image classification technique, this study has used the ASTER data and mapped 299 landslides covering 50.12 km^2 area using Support Vector machine classifier. The contradiction between Kamp et al. (2008), Owen et al. (2008), Lodhi (2011) and this study is because of different time period dataset, spatial extend of study area and the mapping technique of landslides. Saba et al. (2010) has used high resolution data of IKONOS, Quick Bird, SPOT-5 and Worldview-1 for pre and post-earthquake for an area of 36 (km^2) and mapped 158 landslides. Our study has used SPOT-5 dataset and mapped 2421 small and large landslides. Basharat et al. (2014) has used SPOT-5 data to map landslides as point rather polygon and ignore the spatial extend of the landslides area and mapped 1460 landslides covering the area of 1299 (km^2), the current study has used SPOT-5 data for the area of 50.12 $(km)^2$ and mapped 2421 landslides.

Compared to field surveys, remote sensing may have introduce errors due to spatial resolution and landslides which are invisible due to dense vegetation (Lin et al., 2006) . However, the landslides are mostly in rough terrain which makes some areas unreachable and difficult to in-situ observations. High-resolution remote sensing data can give reliable accuracy, but due to high cost it cannot be used for regional studies. Recently the Sentinel-2 data is freely available for all area having 4 bands with spatial resolution of 10 m and temporal resolution of 5 days is the good advancement for the remote sensing researchers which can be used for mapping and monitoring of the landslides. In this study, the Sentinel-2 inventory gives us accuracy of 65%. Now the landslide inventory for regional scale can be developed using 10 m data.

5. Conclusion

This paper contributes to a logical comparison and assessment of five datasets for landslide inventory. Support vector machine classifier (SVM) was applied for the classification of landslides. Five different spatial resolution imageries were taken ranging from 0.4 m to 30 m of different sensors. Our findings demonstrate that the number of landslides detection and accuracy of landslide is decreasing with decreasing the image spatial resolution. It is proved that the high resolution data which is Worldveiw-2 in this study has detected all the small landslides, while the course resolution Landsat-8 data has detected the major landslides. The recently lunched freely available data of Sentinel-2 having spatial resolution of 10 m is worthy source of data for regional based landslide inventory developing and landslide susceptibility mapping. As a final conclusion, the results from this study may be useful for the decision maker to decide which data should be used for the susceptibility mapping.

Authors' Contribution

Muhammad Zeeshan Ali has collected the data, develop all the figure and tables and contributed in write-up of article. Saleem Ullah has review the article multiple times and give scientific suggestion for the improvement of article. Asad Ali helped in writing the paper.

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